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Original Articles

Monitoring changes of NDVI in protected areas of southern California

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ABSTRACT

California's Mediterranean ecosystem has been identified as one of the Earth's biodiversity hotspots. The high degree of rapid urbanization along the southern California coastline has resulted in the loss of significant natural areas over the last century and protected areas that do exist may be further threatened by climate change, drought, and fire. We use Moderate Resolution Imaging Spectroradiometer (MODIS) sensor at a 250 m pixel resolution and the Normalized Difference Vegetation Index (NDVI) to monitor temporal/spatial patterns from 2000 to 2016 within Santa Monica Mountains National Recreation Area and Channel Islands National Park. We test the hypothesis that there should be no significant long-term change in protected areas since 2000 and compare impacts of seasonality, drought, and fire. The Santa Monica Mountains National Recreation Area has experienced a long-term decline in vegetation greenness, vegetation types, and is the most significantly impacted with short-term declines during the summer with or without the impacts of fire. Change detection maps show areas of significant decline in NDVI in the Santa Monica Mountains National Recreation Area especially during the summer. The Channel Islands have relatively stable NDVI possibly due to the removal of non-native herbivores and the maritime climate around the Channel Islands may buffer some of the impacts of the regional drought. The MODIS sensors appears appropriate for identifying landscape patterns, time series, change detection maps, and the potential impacts from climate change for each park. Results suggest that all National Park landscapes and vegetation types can be inventoried at a 250 m resolution and monitored at a high temporal resolution.

1. Introduction

California's Mediterranean ecosystem has been identified as one of the earth's "biodiversity hotspots" (Myers et al., 2000). Though this ecosystem is home to a number of endemic flora and fauna species, it is also one of the most highly altered ecosystems on the planet (Newbold et al., 2016). The high degree of rapid urbanization along the southern California coastline has resulted in the loss of significant natural areas and increasing human impacts to the remaining natural systems (Underwood et al., 2009). Landscape-level threats include urbanization, land cover change, changes to vegetation communities, and climate change (Grimm et al., 2008; Fancy et al., 2009). Global climate change is a concern for protected areas in terms of maintaining ecosystem health, and the impacts must be monitored in order to allow natural resource managers to properly respond and prioritize conservation efforts.

Santa Monica Mountains National Recreation Area and Channel Islands National Park are two of the largest protected areas within California's Mediterranean-type ecosystem. These parks contain high species richness, high endemism, and a high number of species on the International Union for Conservation of Nature Red List (Underwood et al., 2009). Both of these southern Californian protected areas will experience substantial climate change according to global and regional climate models (Cayan et al., 2010; Hall et al., 2012). The higher elevations of Santa Monica Mountains are predicted to warm approximately 1.5 °C by 2060 while temperatures closer to the coast and Channel Islands will be mediated by the local cooling effect of the Pacific Ocean and the maritime effect (Cayan et al., 2010). Predicted climate changes may exacerbate the negative effects of past land use and continued human population growth and many have direct impacts on vegetation condition and community types (Underwood et al., 2009; Anderson et al., 2010; Thoma et al., 2016).

One of the known ecological responses to climate change is a shift in the local phenology of plants such as changes in the start and end of the

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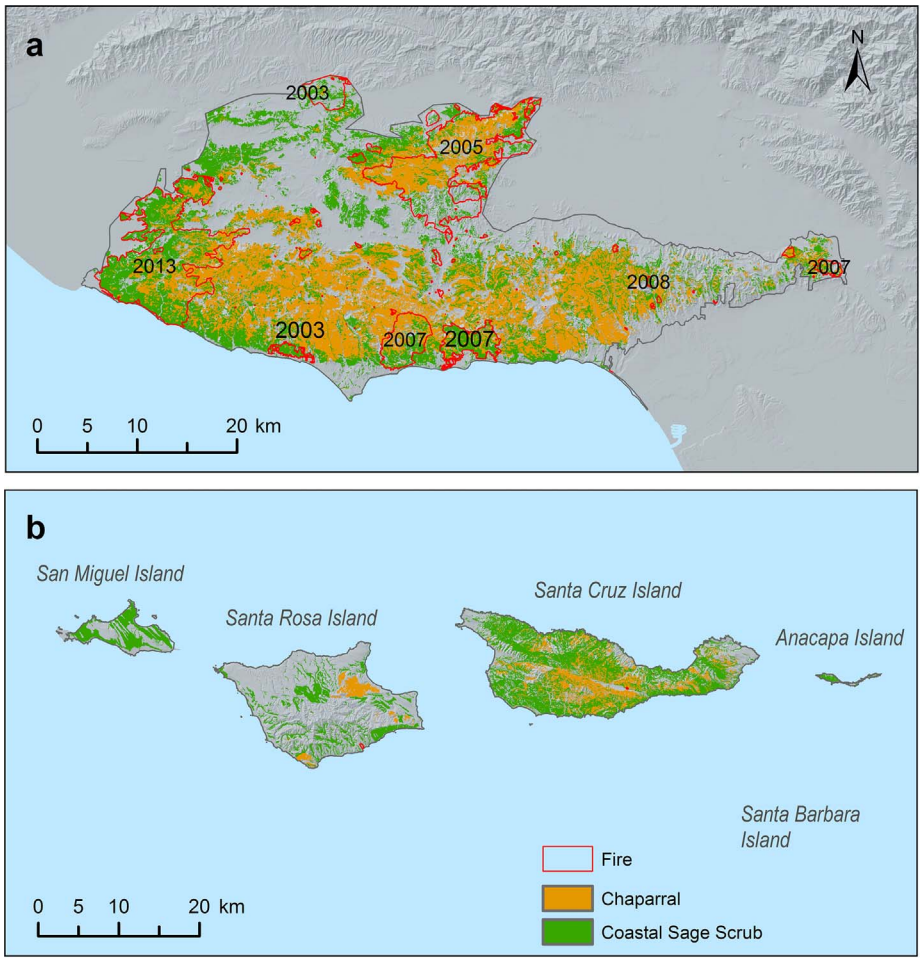

Fig. 1. Maps of the Santa Monica Mountains National Recreation Area (a) and Channel Islands National Park (b). The distributions of chaparral and coastal sage scrub as well as the burned regions during 2000–2016 are also plotted.

growing season, duration of growing season, and maximum productivity (Parmesan and Yohe, 2003). Monitoring phenological changes can help identify the effects of climate change in southern California. Another important impact from climate change is that anthropogenic fires are hypothesized to be becoming more frequent in southern California as the climate warms (Keeley et al., 1999, 2005). These fires are important episodic events, which are unpredictable in time and extent, and can result in rapid and dramatic vegetation change. Fires can fully consume existing stands of shrubland vegetation and create the possibility for dramatic shifts in vegetation composition and species abundances (Keeley et al., 2005).

Remote sensing methods, especially in combination with Geographic Information Systems (GIS) are cost-effective techniques for measuring landscape-level temporal changes over a continuous area (Franklin et al., 2000; Rogan and Chen, 2003). Remote sensing can be used to map changes in land cover type as well as within landscape types and vegetation classes, and is often the primary tool for monitoring landscape changes in protected areas using well established techniques in the remote sensing field (Fraser et al., 2009; Pereira et al., 2013; Willis 2015). In Mediterranean regions, changes in vegetation indices from moderate spectral resolution spaceborne sensors have been significantly associated with plant species richness (Gillespie et al., 2014), live fuel moisture (Roberts et al., 2006; Yebra et al., 2013), post-fire regeneration (McMichael et al., 2004), and plant productivity/stress (Shoshany, 2000). Indeed, moderate resolution imagery from sensors such as NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) may provide a high temporal resolution analysis of protected areas over different spatial and temporal scales. The MODIS sensors on the TERRA and AQUA satellites have 36 spectral bands at 250 m, 500 m, and 1000 m pixel resolution with a nominal revisit time of 1–2 days year-round, making it extremely useful to measure fine-scaled changes in vegetation characteristics and changes in seasonality over time. Protected areas may be monitored from satellite sensors using a vegetation index called NDVI (Normalized Difference Vegetation Index) that is calculated as a function of the visible and near-infrared wavelengths. NDVI ranges from 1.0 to −1.0 with positive values (e.g. 0.5) representing high greenness and negative values (i.e. −0.1) representing little or no vegetation. NDVI represents photosynthetic activity and is associated with biomass, carbon sequestration, plant water stress, and biodiversity (Nagendra et al., 2013; Pereira et al., 2013). Pettorelli et al. (2012) suggested that the NDVI of protected areas, which are less impacted by human activities, can be used to track the effect of climate change on natural ecosystem functioning. There have been an increasing number of studies that have used NDVI to study ecosystem dynamics and disturbance within protected areas (Alcaraz-Segura et al., 2008; Nemani et al., 2009).

There is a need to develop and provide scientifically credible information on the current status and long-term trends in the composition, structure, and function of protected area ecosystems, and to determine how well current management practices are sustaining those ecosystems. This research addressed three primary questions related to monitoring protected areas in Mediterranean ecosystems. First, has there been significant long-term (decadal) declines in NDVI in the Santa Monica Mountain Recreation Area and Chanel Islands National Park and vegetation types? Second, has there been short-term declines in NDVI in protected areas associated with the recent drought and fire? Third, where are the long-term and short-term changes in NDVI within protected areas, and which vegetation types have undergone significant changes?

2. Methods

2.1. Study Area

Coastal southern California has a Mediterranean-type climate, characterized by cool and wet winters and mild to hot dry summers (Barbour et al., 2007; Anderson et al., 2010). The Santa Monica Mountains receive 300–440 mm/year of rain at the base and 500–625 mm in the mountains, with 86% of precipitation occurring between November and March (Harrison et al., 1971). The Channel Islands experience a slightly more maritime climate than the mainland. The rainfall on the Channel Islands is also determined by local topography and elevation, and annually averages 305 mm, with 90% precipitation occurring between November and March. The mean annual temperature on the islands is 15.5 °C, with differences between islands decreasing further west (Anderson et al., 2010).

Santa Monica Mountains National Recreation Area (SAMO) and Channel Islands National Park (CHIS) are managed by the National Park Service (Fig. 1). Chaparral and coastal sage scrub are the largest native plant communities in the Santa Monica Mountains and Channel Islands. Chaparral contains semi-arid shrubs averaging 1.5–3 m high that possess sclerophyllous, generally evergreen leaves and are both drought and fire adapted (Harrison et al., 1971). Typically, chaparral experiences a slight yellowing and leaf loss during the summer from June until November. Coastal sage scrub is distributed along the coast and semiarid inland regions of southern California (Riordan and Rundel, 2009). The coastal sage scrub community is dominated by drought-deciduous short shrubs averaging 1–2 m high that drop leaves during dry summer months as soil water availability decreases, and produce new leaves at the beginning of the winter wet season.

2.2. Remote sensing and GIS data

MODIS data were downloaded using the Reverb on-line database. Data included NASA's Terra MODIS MOD13Q1 250 m tile H08 V05 (Version 5) from February 2000 to January 2017 (herein referred to as 2000–2016). The Normalized Difference Vegetation Index (NDVI) was derived from MODIS MOD13Q1, and is based on the red and near infrared bands to give an estimated greenness, given by:

$$NDVI = (\rho NIR - \rho RED)/(\rho NIR + \rho RED), \quad (1)$$

where ρNIR is reflectance in the near infrared band and ρRED is reflectance in the red band. Each MOD13 tile in the time series was subset by park land areas, and median NDVI value for the regions of interest was calculated per 16-day time step. The 16-day time series was resampled to a monthly time series by averaging the available tiles in each calendar month.

Fire perimeter data was provided by the Department of Forestry and Fire Protection of California. Vegetation polygons were identified as chaparral and coastal sage scrub-dominated areas by California Department of Fish and Wildlife's (CDFW) State Wildlife Action Plan (SWAP) in 2015 (https://www.wildlife.ca.gov/SWAP). The GAPSWAP program provides high spatial resolution data (30-m resolution) with 32 land use/land cover types which can be used to assess native land cover.

2.3. Statistical analyses

We summarized NDVI values for each protected area and major vegetation types for different time periods (entire time series, 2000, 2014, 2015, 2016) that corresponds with long-term (2000–2016) and short-term changes (2014–2016), seasons (March and August), and results with fire and without fire masks. The median NDVI values of the polygons per time step were output as the median time series for SAMO and CHIS, as well as for chaparral and coastal sage scrub of the two parks. Then we calculated the NDVI anomalies for the above six time series by subtracting the long-term 16-day means, by which the seasonal fluctuations were removed while the trend signal remained. Serial correlation, which describes how neighboring values in a series depend on each other, is generally recognized to magnify trends in ecological and hydrological time series (Erasmi et al., 2014; Detsch et al., 2016). To account for such trend overestimations induced by serial correlation, the pre-whitening algorithm described by Yue et al. (2002) was employed to remove the lag-1 autocorrelation in the NDVI time series. Yue et al. (2002) found that the presence of a trend alters the estimate of the magnitude of serial correlation in a time series, and they suggested calculating the lag-1 serial correlation coefficient based on the detrended series and then combining the trend component and modified residual series. Theil-Sen estimator was employed to examine the long-term trends within the six NDVI anomaly time series (Theil, 1950, Sen, 1968). Theil-Sen's slope is regarded as a potential replacement of ordinary least squares for linear regression, which calculates the median of the pair wise slopes of all data points that meet the ranking criteria, and thus it is not sensitive to outliers and requires limited a priori information of measurement errors (Fernandes and Leblanc, 2005). Then Mann-Kendall test, as a robust non-parameter trend detection approach, was used to detect the significance of the greening or browning trends in the pre-whitened time series (Mann, 1945; Kendall, 1975; Hirsch et al., 1982). We also applied BFAST method to analyze the break points and inter-annual trends within the presented NDVI time series (Verbesselt et al., 2010). The BFAST algorithm is essentially an iterative procedure to decompose the NDVI time series (Y) into three additive components of trend (T), seasonality (S) and remainder components (e, noise), which can be expressed by $Yt = Tt + St + et$, $t = 1, \ldots, n$, where t is the time step (16-day in this case). The NDVI maps for the two protected areas in March (as winter imagery) and August (as summer imagery) of the recent years (2014, 2015 and 2016) were compared with the baseline year 2000 during the same months. This identified the NDVI long-term changes from the 2000 baseline. NDVI Z-scores for March and August 2014–2016 (using means during 2000–2016 as baseline) were also mapped to illustrate the short-term NDVI changes. The Z-score maps with unit of standard deviation are more appropriate to compare the spatial patterns of the NDVI anomalies.

Multiple linear regressions were used to identify significant changes of NDVI in the recent years (2014–2016) as compared to the baseline year 2000. We also identify if there are significant changes in NDVI during the wet and dry seasons (March/August), for different vegetation types (chaparral, coastal sage scrub) and the impact of wildfire (burned/unburned) in time and space. We would expect that there would be no significant changes in NDVI across the wet and dry season, the dynamics will be similar for different vegetation types (chaparral and coastal sage scrub), and burned areas should has lower NDVI than unburned areas.

Lin et al. (2013) argued that even minuscule effects can become statistically significant when we apply small-sample statistical inference to large samples. Linear regression cannot avoid this kind of p-value problem, which has long been aware of by statisticians (Chatfield, 1995). Analysis of remote sensing datasets is carried out on a pixel-based approach and large samples at high-resolution can easily capture small but statistically significant effects from environmental factors. It is supported by our initial results that all the variables (drought year, season, vegetation type and fire) showed significant contribution ($p < 0.05$) in the multiple linear regression model when all the pixels (22,762 for SAMO, 8,710 for CHIS) were included. Therefore, bootstrapping was performed to resample the original data and to reduce the sample size. In this study, 500 pixels were randomly selected from all the 22,762 pixels in SAMO to conduct the linear regression

Table 1
NDVI statistics of the time series (February 2000 to January 2017) for Santa Monica Mountains National Recreation Area (SAMO) and Channel Islands National Park (CHIS) over the unburned regions.

Park and year	Mean	Standard deviation	Min	Max
SAMO				
NDVI entire time series	0.511	0.074	0.376	0.694
NDVI for 2000	0.526	0.060	0.459	0.647
NDVI for 2016	0.444	0.068	0.377	0.598
CHIS				
NDVI entire time series	0.399	0.111	0.259	0.680
NDVI for 2000	0.389	0.101	0.288	0.581
NDVI for 2016	0.367	0.094	0.275	0.542

computations, while the sample size was reduced to 300 for CHIS which only have a total of 8,710 pixels. The above processes were repeated for 1000 bootstrapping replications, and the distribution as well as the medians of the statistics (regression slopes and p-values) were obtained after the iteration. The analyses for winter (March) and summer (August) were conducted separately. First, a linear regression model was used to detect whether drought year and vegetation type induced impacts on the NDVI variations in SAMO, and the interaction between the two factors was also observed. Then a similar regression model was applied while the effects from drought year and wildfire as well as their interaction were examined. The explanatory variables of drought year, vegetation type and fire occurrence in the two linear regression models were all set as categorical variables while the response variable NDVI for both was a continuous variable. As the independent variables (drought year, vegetation type, and fire history) are very different in scales, we thus set them as dummy variables in the two regression models. The regression slopes indicate the relative changes of NDVI for the specific groups compared to the reference group. Therefore, the regression slopes for different groups can be compared with each other, and we do not need to standardize the regression slopes. In addition, we also tried to include the three independent variables into one regression model. However, the three-variable interactions (drought year, vegetation type, and fire) were all not significant. Moreover, as CHIS only had negligible burned area (Fig. 1), thus we decided to use two regression models to examine the impacts of fire and vegetation types separately, and the linear regressions accounting for fire disturbance were only conducted in SAMO. The two regression models containing dummy variables that indicate drought year, vegetation type and fire presence were expressed as:

$$NDVI_{ijk} = \beta_0 + \sum_{i=1}^{3} \beta_{Yi} Y_i + \sum_{j=1}^{2} \beta_{Vj} V_j + \sum_{i=1}^{3} \sum_{j=1}^{2} \beta_{ij} Y_i V_j + \varepsilon_{ijk} \quad (2)$$

where $NDVI_{ijk}$ is the average NDVI of a vegetation type in March (or August) of a particular year; β_0, β_{Yi}, β_{Vj} and β_{ij} are the regression coefficients; ε_{ijk} is random error. Dummy variables $Y_1 - Y_3$ indicating drought year were assigned binary values as follows:

Y_1	Y_2	Y_3	
0	0	0	if observation is for 2000
1	0	0	if observation is for 2014
0	1	0	if observation is for 2015
0	0	1	if observation is for 2016

Dummy variables V_1 and V_2 indicating vegetation type were assigned binary values as follows:

V_1	V_2	
0	0	if observation is for other vegetation
1	0	if observation is for chaparral
0	1	if observation is for coastal sage scrub

$$NDVI_{ik} = \beta_0 + \sum_{i=1}^{3} \beta_{Yi} Y_i + \beta_F F + \sum_{i=1}^{3} \beta_{FYi} Y_i F + \varepsilon_{ik} \quad (3)$$

where $NDVI_{ik}$ is the average NDVI of the burned (or unburned) region in March (or August) of a particular year; β_0, β_{Yi}, β_F and β_{FYi} are the regression coefficients; ε_{ik} is random error. Dummy variables $Y_1 - Y_3$ indicating drought year are assigned binary values as same as above. Dummy variable F refers to the burned ($F = 1$) or unburned ($F = 0$) region during 2000–2016. The bootstrapping regression coefficients of the above two linear regression models were used to measure the quantitative effects from drought year, vegetation type and fire. The p-values could determine whether a factor showed statistical significance. As the statistics of interest were obtained based on the data from only 500 pixels in SAMO and 300 pixels in CHIS in each replication of the bootstrapping, not all the independent variables showed significant contribution, which helps us compare the relative importance among the multiple factors.

3. Results

3.1. NDVI trajectory

Santa Monica Mountains National Recreation Area had the highest mean NDVI value of 0.511 (standard deviation 0.074) over the unburned regions, followed by Channel Islands National Park that had a mean of 0.399 (standard deviation 0.111) (Table 1). NDVI values highlighted a number of temporal fluctuations in greenness in both protected areas in southern California from 2000 to 2016 (Fig. 2). SAMO shows the highest NDVI values over time with the peak NDVI generally after the February and the annual variation is generally within a NDVI range of 0.6 and 0.5. CHIS shows lower NDVI values and greater swings in NDVI values annually. The peak in NDVI in CHIS is generally on or before February and the annual variation in NDVI generally ranges from 0.6 to 0.3. The trend detection using Theil-Sen

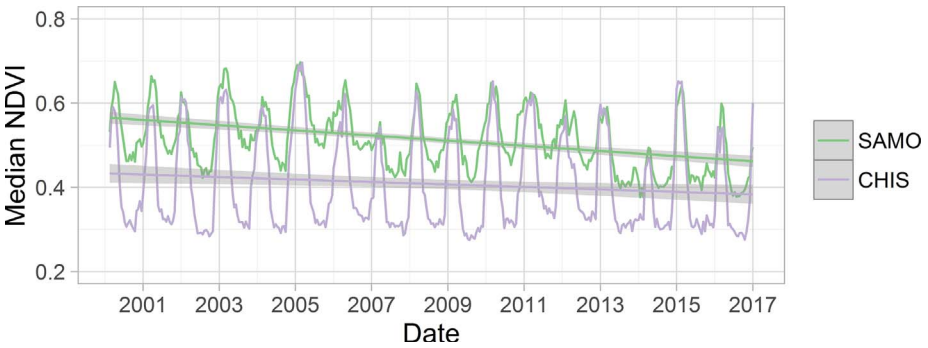

Fig. 2. Time series of MODIS NDVI values of all the months of the year for Santa Monica Mountains National Recreation Area (SAMO) and Channel Islands National Park (CHIS). Linear trends and 95% confidence intervals for the two time series are also plotted.

Table 2
Trends (NDVI change per year) of the NDVI time series using Theil-Sen estimator and Mann-Kendall test for Santa Monica Mountains National Recreation Area (SAMO) and Channel Islands National Park (CHIS).

NDVI Series	Sen's slope	Kendall's tau	*p*-value	Linear trend
SAMO	−0.0058	−0.114	0.001	−0.0059
SAMO (chaparral)	−0.0068	−0.138	0.000	−0.0070
SAMO (coastal sage scrub)	−0.0068	−0.107	0.002	−0.0069
CHIS	−0.0021	−0.040	0.238	−0.0025
CHIS (chaparral)	0.0007	0.016	0.628	0.0004
CHIS (coastal sage scrub)	−0.0012	−0.032	0.353	−0.0015

estimator and Mann-Kendall test suggests that the NDVI values of SAMO have experienced significant decline ($p < 0.05$) with a browning trend of −0.0058 per year, i.e. a decrease of 0.095 in NDVI over the 17 years (Table 2). However, no significant NDVI trend was observed for CHIS (Table 2).

The NDVI dynamics of the native vegetation types (chaparral and coastal sage scrub) in SAMO and CHIS were examined (Fig. 3). Patterns of chaparral and coastal sage scrub are similar to regional overall NDVI patterns. Chaparral has higher NDVI values and less seasonal variability than coastal sage scrub. Both have significantly decreased in SAMO from 2000 compared to present, while the two vegetation types did not display significant changes in CHIS (Table 2).

The results of BFAST analysis indicate that no seasonal or phenological changes have occurred in SAMO or CHIS during 2000–2016, as the seasonal components of the NDVI time series for the two parks kept consistent in this period (Fig. 4). However, the seasonal component of CHIS showed bigger amplitude and narrower NDVI peaks, due to the dominated coastal sage scrub community. There were three significant breakpoints in the NDVI trend components of both SAMO and CHIS (Fig. 4). The dates of the breaks of the two time series were similar. There was a significant NDVI increase in October 2004 ($p < 0.05$), before which the NDVI in the two parks kept stable. Then a steep declining trend occurred between October 2004 and February 2008 ($p < 0.05$), which should be induced by the 2007–2008 drought in California. A significant NDVI rebound was observed in 2008 winter ($p < 0.05$), followed by a slight increasing trend ($p < 0.05$, only in CHIS). In March 2013, an abrupt NDVI drop was captured ($p < 0.05$), which was related to the recent drought. Though a slow greenness recovery (not significant) has been detected, the average NDVI values for the two parks still remain at low levels during the past three years.

3.2. Spatial patterns and seasonal differentiation of NDVI change

Using NDVI in 2000 as a baseline, the NDVI changes in March (winter imagery) and August (summer imagery) during the past three years (2014–2016) were mapped for SAMO (Fig. 5) and CHIS (Fig. 6), respectively. In 2014, summer imagery of SAMO shows overall declines in NDVI but declines were not as great as winter declines in NDVI. In 2015 and 2016, winter imagery indicates quick vegetation recovery while it did not happen in summer. The most striking NDVI decrease in SAMO was observed at the western and northern section. There has been a general decline in NDVI since 2000 for CHIS, however, the decline was not as extreme as SAMO. In CHIS, the greatest decline has occurred during the winter with declines of > 0.2 over Santa Rosa Island, low lying areas in Santa Cruz Island, and eastern San Miguel Island (Fig. 6).

The NDVI Z-score maps illustrate the standardized NDVI anomalies for the two parks during the recent drought, with the baseline of 2000–2016 (Figs. 7 and 8). Similarly, the severest declines occurred in the winter of 2014, followed by apparent greening in winter of 2015 and 2016 except for southern fringes of CHIS in 2016 March. The greenness in southwestern SAMO decreased more than 3 standard deviations in 2014 March compared to the average levels during 2000–2016, which was partly caused by the Spring fire in 2013. In summer, declines were aggravated by the exceptional drought from 2014 to 2016 in both the two parks.

3.3. Impacts from vegetation type and fire

The linear regressions accounting for vegetation impacts showed some difference between SAMO and CHIS (Tables 3 and 4). In SAMO, only the NDVI in 2014 showed significant declines ($p < 0.05$) in March, compared to the baseline of 2000 March; the NDVI of SAMO in winter rebounded to average levels in 2015 and 2016 ($p > 0.05$) (Tables 3 and 4). The winter NDVI of CHIS experienced significant declines from 2014 to 2016. In summer, the NDVI in all the recent three years 2014–2016 showed significant declines ($p < 0.05$) in the two parks. The severest 2014 winter browning induced an average NDVI decline of about 0.10 over the entire SAMO and 0.15 for CHIS, while the greatest summer declines were about 0. 06 for SAMO and 0.04 for CHIS in 2016. When we consider the impact from vegetation type, chaparral and coastal sage scrub both showed significantly higher NDVI than the other communities ($p < 0.05$) in SAMO, but significantly lower NDVI than the other vegetation types ($p < 0.05$) in CHIS. The large proportions of developed lands in SAMO might depress the NDVI levels for the other vegetation types. Besides, chaparral demonstrated higher NDVI than coastal sage scrub, especially in summer, which is related to the continuing photosynthesis of chaparral in dry season (Tables 3 and 4). Chaparral and coastal sage scrub both displayed significantly severer NDVI decrease in 2014 than the other vegetation type

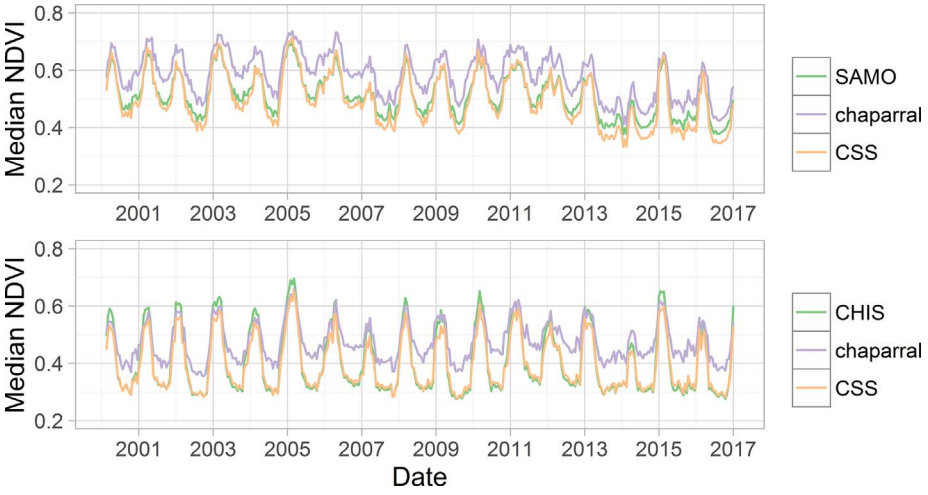

Fig. 3. MODIS NDVI values of all the months of the year for vegetation zones of chaparral (chap) and coastal sage scrub (CSS) in Santa Monica Mountains Recreation Area (upper) and Channel Islands National Park (lower).

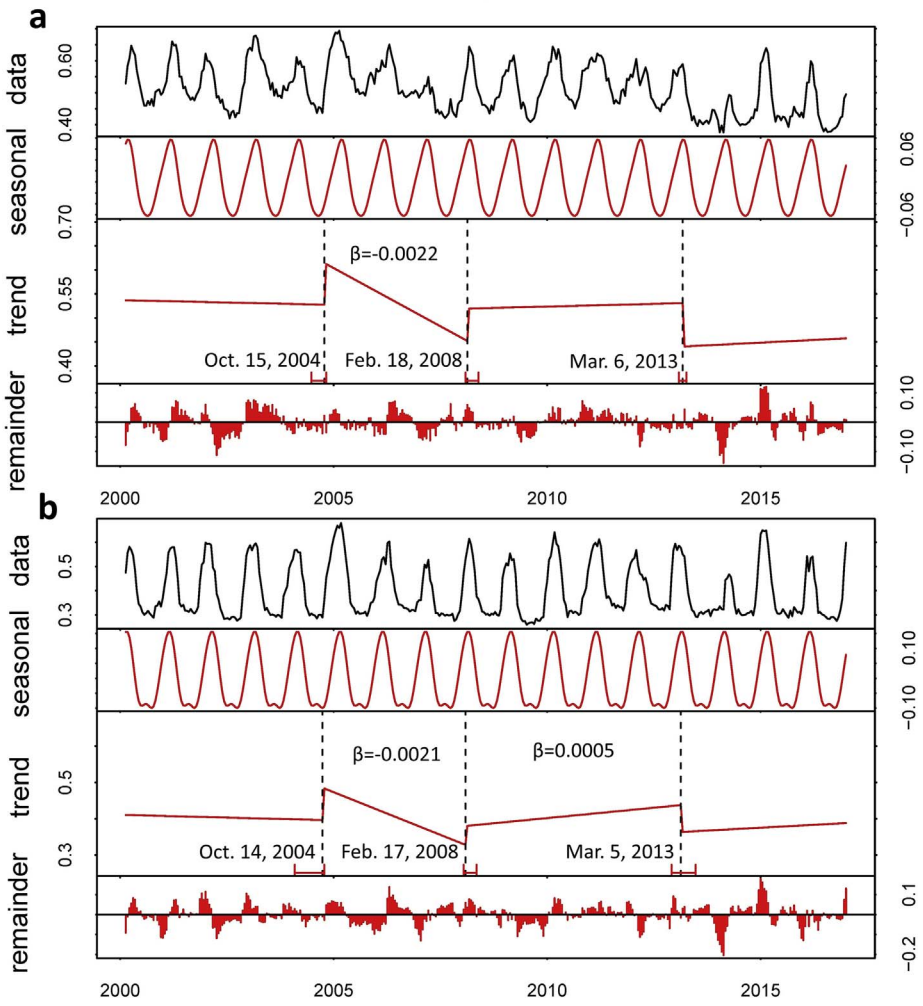

Fig. 4. BFAST decomposed seasonal, trend and remainder (i.e. estimated noise) components for the 16-day MODIS NDVI time series of SAMO (a) and CHIS (b). The detected breakpoints with 95% confidence interval and significant slopes ($p < 0.05$) of the gradual changes of the trend components are indicated.

(mostly developed land cover) in SAMO, but not in 2015 and 2016. However, the chaparral and coastal sage scrub communities in CHIS showed significantly (winter) or insignificantly (summer) higher NDVI than the other vegetation (mostly grassland).

The regions with fire occurrence showed significantly higher NDVI than the unburned regions in March of SAMO for 2000 to 2016 ($p < 0.05$) (Table 5). It should be caused by the elevated winter NDVI in 2000 over the regions that were burned afterwards. In March, fire history showed additive disturbance to the declined NDVI in 2014 ($p < 0.05$), but it was not observed in 2015 and 2016 (Table 5). In August, fire presence significantly contributed to the declines from 2014 to 2016 ($p < 0.05$); however, the fire disturbance decreased gradually.

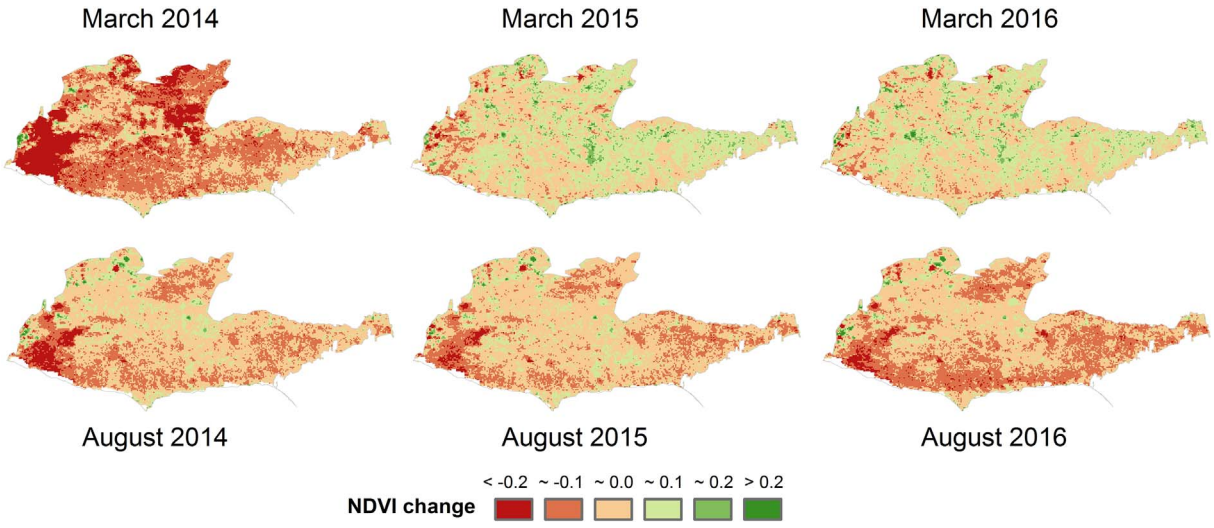

Fig. 5. Long-term change detection in MODIS NDVI for Santa Monica Mountains National Recreation Area during March and August of 2014–2016 with the baseline of 2000.

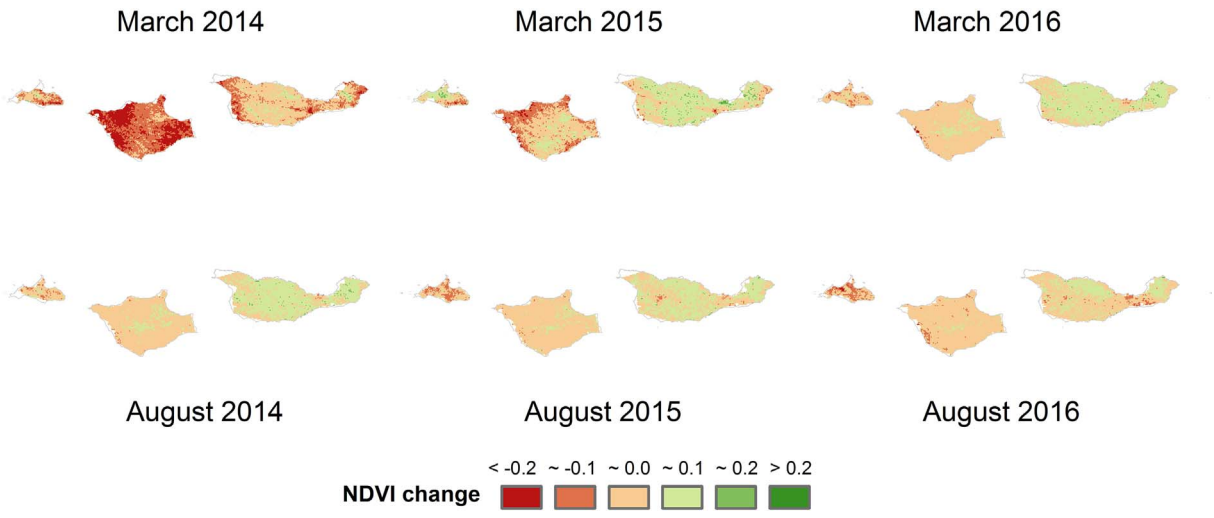

Fig. 6. Long-term change detection in MODIS NDVI for Channel Island National Park during March and August of 2014–2016 with the baseline of 2000.

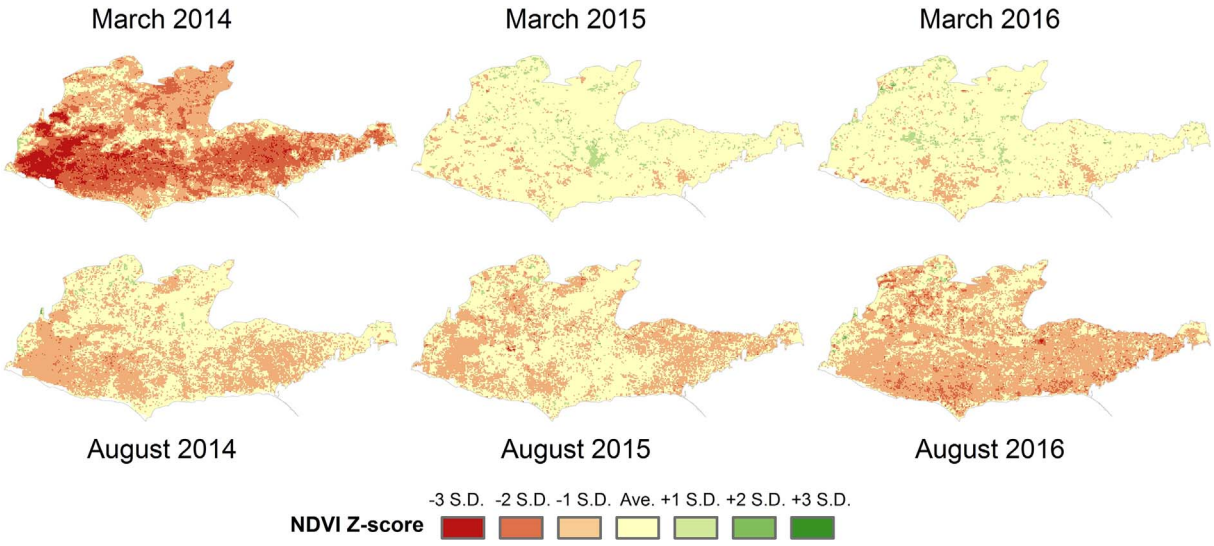

Fig. 7. MODIS NDVI Z-score maps for Santa Monica Mountains National Recreation Area during March and August of 2014–2016 with the baseline of 2000–2016.

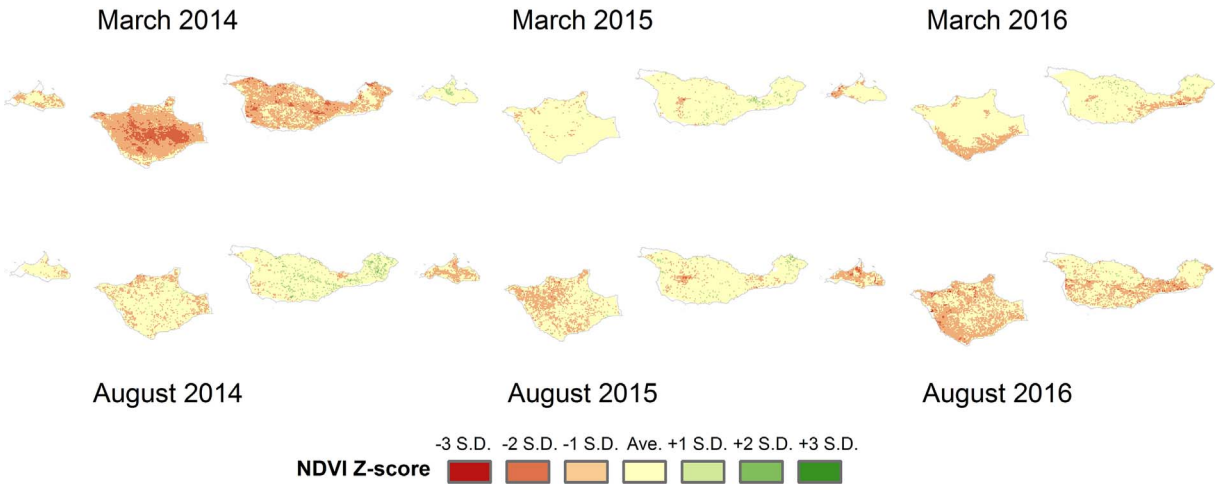

Fig. 8. MODIS NDVI Z-score maps for Channel Island National Park during March and August of 2014–2016 with the baseline of 2000–2016.

Table 3
Medians of the bootstrapping regression slopes and *p*-values of the multiple linear regressions on NDVI, monitoring year and vegetation types (chaparral and coastal sage scrub (CSS)) for SAMO. Significant median slopes ($p < 0.05$) are in bold.

Groups	β (Mar)	*p* (Mar)	β (Aug)	*p* (Aug)
NDVI (β_0) (2000 other)	**0.547**		**0.439**	
2014	**−0.097**	0.000	**−0.037**	0.000
2015	0.004	0.591	**−0.044**	0.000
2016	0.004	0.623	**−0.058**	0.000
Chaparral	**0.088**	0.000	**0.094**	0.000
CSS	**0.050**	0.000	0.009	0.325
2014 chaparral	**−0.054**	0.000	**−0.059**	0.000
2015 chaparral	−0.012	0.376	**−0.034**	0.015
2016 chaparral	−0.019	0.174	**−0.054**	0.000
2014 CSS	**−0.071**	0.000	**−0.044**	0.003
2015 CSS	−0.014	0.342	−0.028	0.063
2016 CSS	−0.017	0.259	**−0.034**	0.023

Table 4
Medians of the bootstrapping regression slopes and *p*-values of the multiple linear regressions on NDVI, monitoring year and vegetation types (chaparral and coastal sage scrub (CSS)) for CHIS. Significant median slopes ($p < 0.05$) are in bold.

Groups	β (Mar)	*p* (Mar)	β (Aug)	*p* (Aug)
NDVI (β_0) (2000 other)	**0.604**		**0.324**	
2014	**−0.152**	0.000	**−0.017**	0.047
2015	**−0.047**	0.000	**−0.025**	0.003
2016	**−0.067**	0.000	**−0.038**	0.000
Chaparral	**−0.063**	0.000	**0.083**	0.000
CSS	**−0.085**	0.000	0.003	0.500
2014 chaparral	**0.101**	0.000	**0.045**	0.019
2015 chaparral	**0.071**	0.003	0.032	0.097
2016 chaparral	**0.066**	0.005	0.012	0.520
2014 CSS	**0.059**	0.000	0.015	0.275
2015 CSS	**0.045**	0.007	0.010	0.440
2016 CSS	**0.042**	0.013	0.010	0.469

Table 5
Medians of the bootstrapping regression slopes and *p*-values of the multiple linear regressions on NDVI, monitoring year, and fire occurrence for SAMO. Significant median slopes ($p < 0.05$) are in bold.

Groups	β (Mar)	*p* (Mar)	β (Aug)	*p* (Aug)
NDVI (β_0) (2000 unburned)	**0.577**		**0.478**	
2014	**−0.106**	0.000	**−0.053**	0.000
2015	0.001	0.715	**−0.053**	0.000
2016	−0.004	0.532	**−0.075**	0.000
Burned	**0.035**	0.001	**−0.040**	0.000
2014 burned	**−0.117**	0.000	**−0.056**	0.000
2015 burned	−0.021	0.157	**−0.040**	0.006
2016 burned	−0.009	0.544	**−0.033**	0.025

4. Discussion

4.1. Time series

In this study, we utilized MODIS NDVI data to examine long and short terms changes and the impacts of the recent California drought on the vegetation greenness of two National Parks. Due to the limited timespan of MODIS imagery, the NDVI in 2000 was selected as a baseline for change detection. The annual mean NDVI in 2000 for the unburned regions of the two parks were 0.526 (SAMO) and 0.389 (CHIS), while the overall means before the recent drought (2000–2011) for SAMO and CHIS were 0.531 and 0.404, respectively. Thus, we assumed the NDVI in 2000 could represent the normal greenness conditions of the two parks in the early years of the 21st century. However, the greenness baselines for the period before 2000 were not included due to limited data availability, which is a shortcoming of this study.

Based on our analysis, there has been a significant decline in NDVI since 2000 in SAMO. This suggests the photosynthetic activity, plant water content, and carbon uptake has also declined during this time period (Nagendra et al., 2013; Pereira et al. 2013; Pettorelli 2013). SAMO appears to be more significantly impacted of the two parks. Peak NDVI values for SAMO after 2013 are below the averages of natural variation for the time series. CHIS has remained more stable over the time series. Although peak values in NDVI are lower in 2014, the low annual values in NDVI (e.g. 0.36) are similar to 2000 in CHIS. This suggests that the maritime climate around the Channel Islands may buffer some of the impacts of the regional drought. Time series of vegetation indices such as NDVI and associated metrics, such as primary productivity and photosynthetic capacity, are an integrated way to measure diversity and vegetation condition and have important implications for protected areas.

4.2. Change detection maps

The greatest decline in NDVI occurred during the 2014 winter, indicating a severe browning of vegetation in this exceptional drought. Although NDVI rebounds were observed for the winters of 2015 and 2016, the continuously decreased greenness during the summers from 2014 to 2016 suggests that the drought disturbance has not been completely relieved. Indeed, change detection shows both the extended drought and the May 2, 2013 Springs Fire that burned more than 97.2 km^2 in the western end of the Santa Monica Mountains. The Springs Fire was unprecedented in size and burned in spring rather than the peak dry season in summer or fall. This also suggests that SAMO is more prone to fire, likely due to the low water content in the native vegetation. Winter MODIS imagery shows the declines of > 0.2 in NDVI over Santa Rosa Island, low lying areas in Santa Cruz Island, and western San Miguel Island. These changes are related to decreases in NDVI over non-native grasslands. A similar pattern of decline in NDVI can be seen during August, however, the declines are not as extreme as compared to winter. Santa Cruz shows increases in NDVI in the central highlands and eastern section of the island. This may be due to the removal of non-native fauna on the entire island, which has results in the return of native vegetation types.

Change detection maps are a powerful way to identify high priority areas. Change detection maps can be created to compare annual and seasonal changes between the 2000 baseline and present. These longer-term data identify locations that experience changes and cumulative changes in the landscape such as land cover development in the Santa Monica Mountains. NDVI Z-score maps that identify greenness anomalies can be used to compare the vegetation greening and browning in space, and they have may be of importance as priority areas of field monitoring for natural resource managers.

The integration of bootstrapping and multiple linear regression showed high performance in quantify the effects of environmental factors on the vegetation dynamics. The interaction of drought year and vegetation type suggests that the native chaparral and coastal sage scrub in SAMO both experienced more browning than the other communities in summer from 2014 to 2016. The fire disturbance was also more obvious in summer as shown by the linear regressions. Therefore, the environmental factors seem to induce more differentiations to vegetation in dry season due to water scarcity.

4.3. Vegetation change

Drought has significantly impacted the native vegetation in Santa Monica Mountains which is now highly vulnerable to fire based on time series and change detection maps. Native chaparral and coastal sage scrub ecosystems are experiencing declines in greenness not seen over the last 17 year time series with unprecedented low levels of vegetation productivity in 2014. If the drought continues there may be mortality of certain species within these vegetation types in the future. NDVI change detection for 2015 and 2016 can identify areas in SAMO that have

returned to pre-drought conditions, areas of no change, or identify areas still declining in greenness that might be extremely vulnerable to fire due to plant water stress in the spring or summer. Similar analyses can be undertaken for CHIS along with assessment of the impact of non-native fauna removal on native and non-native vegetation types on Santa Cruz and Santa Rosa.

4.4. Management implications

For some of the variables measured, such as phenology or changes in NDVI associated with plant water stress, it is not possible to manage these phenomena. For instance, the decrease in greenness due to drought in chaparral cannot be overcome by watering based on park management practices. However, vulnerable vegetation types and regions can be identified, prioritized, and field based assessments can be undertaken to identify if mortality in native species are occurring in areas with high declines in NDVI. The strong browning in southern coast of SAMO, western San Miguel Island, southern Santa Rosa Island and eastern Santa Cruz Island should be particularly monitored in the coming years.

Identifying and monitoring the spatial distribution of change is important for natural resource managers. Inventories using MODIS NDVI such as in this study are ideal for monitoring high temporal resolution change patterns from the 2000 baseline at 250 m pixel resolution. This may be the best manner in which to comparatively monitor changes for all National Parks at a coarse scale but in near real time. NDVI can be used to inventory locations and areas as a baseline for comparisons of significant change. Changes in NDVI of > 1 SD (standard deviation) at 250 m pixel resolution may be determined as moderate greening/browning in Mediterranean protected areas. Accordingly, changes of > 2 SD and > 3 SD maybe defined as severe greening/browning and extreme greening/browning, respectively. A change of > 1 SD is associated with a meaningful increase or decrease in photosynthetic activity and should be associated with changes in biomass, carbon storage, plant water stress, and biodiversity. The 250 m pixel size is a large area and significant changes at this pixel size may have a significant impact of ecosystem structure or function. The MODIS NDVI data within parks and vegetation types can be further examined when overlaid on Google Earth (Appendix A and B). This provides natural resource managers with large area data on places that are significantly changing and a simple way to examine and interpret the data. There have also been developments on combining and comparing information from multiple sensors and net primary productivity that could help address potential limitations from using a single sensor in the future (Crabtree et al., 2009; Wang et al., 2017).

5. Conclusions

NDVI from spaceborne sensors appears appropriate for identifying landscape patterns and time series for Mediterranean protected areas like the Santa Monica Mountains National Recreation Area and the Channel Islands National Park. MODIS NDVI provides a baseline or benchmark from the beginning of the century on the status of protected areas and provides daily imagery that can be used to update time series and change detection results in the future. Establishing baseline NDVI values and monitoring time series, change, and phenology should be a standard practice throughout the National Park system. All National Parks can be inventoried and monitored since 2000 using time series and change detection undertaken in this research and provide summary statistics for National Parks along with time series analyses and change detection maps. GIS layers of special interest could also be examined for all National Parks. It should be possible to integrate NDVI inventory and monitoring information into planning, management, and decision-making.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolind.2018.01.031. These data include Google maps of the most important areas described in this article.

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